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The Potential of LLM-Based AI Chatbots as a Supporting Tool for RSM Analysis in Biodegumming

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Abstract

Background: The development of optimization models in the biotechnology industry, particularly for the biodegumming of bast fiber plants, requires statistical approaches to determine optimal conditions, and Response Surface Methodology (RSM) is one of the most frequently applied models. However, conventional software such as RStudio is complex for beginners, so supporting tools are needed to assist data interpretation.
Aims: This study aimed to evaluate the capability of generative artificial intelligence (AI) chatbots, namely OpenAI ChatGPT (GPT-5.2) and Google Gemini (Gemini 3 Flash), in interpreting RSM data.
Methods: A qualitative–quantitative approach with a descriptive comparative analysis was employed. Secondary data from 35 experimental runs with two independent factors, previously analyzed by RSM in RStudio, were used. The R^2 values, model significance, and lack-of-fit status generated by the AI models were compared with the deterministic outputs of RStudio (regression coefficients, ANOVA table, R^2, and lack-of-fit test).
Result: Both AI models were able to identify the model structure and general response patterns, and their R^2 values (43.6–44.6%) were close to that of RStudio (44.4%); however, numerical differences remained, particularly in the predicted optimum conditions. The effectiveness of the interpretation was strongly influenced by the structure of the prompt.
Conclusion: Both AI models have the potential to serve as tools for interpreting RSM data, but verification with conventional statistical software remains necessary because of their limitations in performing regression calculations.

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1. Introduction

The increasing demand for fibers has led the textile industry to seek natural fibers as alternatives, including jute, kenaf, and ramie (Duan *et al.*, 2016; Przybek, 2025; Wulandari *et al.*,

2021). Natural fibers consist of two components, cellulose and non-cellulose, which are bound together by a gum in the form of pectin (Horikoshi *et al.,* 2021). The desired natural fiber generally has a high cellulose content. Therefore, the two components must be separated, which remains a challenge in natural fiber production. Biodegumming is an alternative green-process technique that separates cellulose from non-cellulose components through the degradation of pectin by microbial agents (Subash & Muthiah, 2021; Wulandari *et al.,* 2021). Pectin is a complex, sticky polysaccharide composed of galacturonic acid monomers, which serves as a supporting component in natural bast plants (Obomighie *et al.,* 2025).

The separation of cellulose from non-cellulose components begins with the degradation of pectin through chemical reactions catalyzed by pectinase enzymes (Chiliveri *et al.,* 2016). Pectinase breaks down the polysaccharide into galacturonic acid monomers through various reactions, such as de-esterification and the cleavage of glycosidic bonds (Oumer, 2017). Consequently, pectinase plays an important role in biodegumming. Various microbes have been reported to produce pectinase for biodegumming, including *Rhizopus* sp., *Penicillium* sp., and *Pectobacterium* sp. (Duan *et al.,* 2016; Wulandari *et al.,* 2021). However, the optimum conditions for pectinase production are still being developed because each microbial species has different physiological requirements.

Various optimization approaches have been applied, one of which uses experimental designs to vary environmental factors such as temperature, pH, and biodegumming time (Chowdhury *et al.,* 2017; Duan *et al.,* 2021). Experimental designs can be facilitated by various statistical applications, which helps to reduce costs. In biotechnology, Response Surface Methodology (RSM) is one of the most widely used models because it can simultaneously predict the optimum point, factor combinations, and interactions between factors (Veza *et al.,* 2023). In addition, RSM can accurately predict mathematical models, which benefits the biotechnology industry in product development as well as in reducing energy use and costs (Lamidi *et al.,* 2023).

RSM can be performed using several applications, such as RStudio, Design-Expert, and Minitab. Among these, RStudio is an attractive alternative because it is open-source and free of charge (Veza *et al.,* 2023). A study by Gonçalves *et al.* (2012) reported the capability of RStudio in building an RSM design, with an R^2 value of 44%, indicating that approximately 44% of the response variation could be explained by the modeled factors. Based on the data of Gonçalves *et al.* (2012), substrate concentration and reaction time had a relatively moderate effect on enzyme activity, suggesting that other factors outside the model influenced the response. Nevertheless, this model was used as the basis of analysis in the present study.

RStudio has several drawbacks for beginners or basic users, including the technical complexity of designing and the difficulty of understanding RSM designs (Hackenberger, 2020; Montgomery, 2017). Therefore, an affordable and user-friendly supporting tool with the potential to interpret RSM data is needed.

Artificial intelligence (AI) is currently a widely discussed phenomenon. The industrial revolution is transforming toward AI-based systems, in which AI is involved in problem-solving processes such as data analysis. One form of AI application is the open chatbot. Chatbots are designed to mimic human conversation through informative text- or voice-based interactions (Labadze *et al.,* 2023). Among the most widely discussed chatbots are OpenAI ChatGPT and Google Gemini. ChatGPT, developed by OpenAI, is regularly trained on large-scale text and code data derived from books and articles (Labadze *et al.,* 2023). Meanwhile, Gemini is a bot developed by Google that applies Large Language Model (LLM) and Natural Language Processing (NLP) technologies; therefore, it can be used as a deep learning medium and is more educational for academics (Imran & Almusharraf, 2024).

A key element in the use of AI is the prompt. In the context of AI, a prompt refers to the instruction entered by a human user. AI can imitate human speaking style, structure, writing quality, and analysis. However, although its output appears "human-like," AI requires a human user to build concepts and creative understanding. AI still requires human direction, assistance,

and interpretation to read existing data patterns. Therefore, AI is a supporting tool rather than a substitute for human reasoning (Dwivedi *et al.,* 2023). One form of user creativity lies in constructing appropriate prompts so that the analyses and answers of AI chatbots are accurate.

Although open AI chatbots have potential as an alternative for data interpretation, no previous study has reported their use for this purpose. Based on this background, this article addresses two research questions: (1) What prompt structure is effective for producing RSM data interpretation using LLM-based AI chatbots? (2) How deep is the capability of generative AI (ChatGPT and Gemini) in interpreting RSM compared with conventional statistical software (RStudio)? The aim of this article is to evaluate the potential of AI chatbots in analyzing and interpreting statistical data, particularly in designing Response Surface Methodology (RSM) models for the development of biotechnology.

2. Methods

This study employed a comparative design with a qualitative–quantitative approach. The method used was AI-driven secondary data analysis, and the results are presented descriptively and comparatively.

2.1 Preparation of AI Chatbots

The tools used in this study were two open chatbots, namely ChatGPT (model GPT-5.2) and Google Gemini (model Gemini 3 Flash). These two chatbots were selected because they are easily accessible and publicly available without a paid license. In addition, both chatbots had high popularity indices in 2024–2025. The free versions of both chatbots were used in this study. Registration on both chatbots was carried out using an e-mail account. The data used for the modeling simulation were taken from the study by Gonçalves *et al.* (2012); only the data table was entered into the AI, without the title, abstract, or any other information identifying the previous study. Both chatbots were accessed from 10 to 15 September 2025.

2.2 Preparation of Secondary Data

The data were adapted from the study by Gonçalves *et al.* (2012), who used the statistical software RStudio to build the RSM model (Table 1). The response tested was the activity of pectin lyase (PL) produced by *Penicillium* sp. The study used a 5 × 5 full factorial design with two factors, namely substrate composition and cultivation time. A modification was applied to the 10 g/L substrate level, which was replicated three times. The data include experimental and predicted values. The experimental values are laboratory validations, whereas the predicted values are the outputs of the mathematical model. Both components are important when designing an RSM model. The data were entered into Excel format, uploaded as an Excel file (.xlsx) into the chat column of each chatbot, and then generated together with the prompt.

Table 1. RSM model design with a 5 × 5 full factorial (Gonçalves *et al.,* 2012)

No	Substrate (g/L)	Time (h)	Experimental production	Estimated production
1	5	24	388	622
2	5	48	1437	1294
3	5	72	1093	1648
4	5	96	1017	1686
5	5	120	288	1406
6	10	24	332	1131
7	10	48	2142	1803
8	10	72	1582	2157
9	10	96	2258	2195
10	10	120	1638	1915
11	10	24	1425	1131
12	10	48	2615	1803

No	Substrate (g/L)	Time (h)	Experimental production	Estimated production
13	10	72	2491	2157
14	10	96	2418	2195
15	10	120	2274	1915
16	10	24	1353	1131
17	10	48	2847	1803
18	10	72	2394	2157
19	10	96	2382	2195
20	10	120	3111	1915
21	15	24	1329	1330
22	15	48	2290	2002
23	15	72	2883	2357
24	15	96	3203	2394
25	15	120	2887	2115
26	20	24	533	1220
27	20	48	913	1892
28	20	72	1293	2247
29	20	96	1013	2284
30	20	120	1061	2005
31	30	24	440	73
32	30	48	1077	744
33	30	72	1153	1099
34	30	96	1057	1137
35	30	120	1393	857

2.3 Prompt Preparation and Experimental Design

At this stage, two main workflows were carried out: prompt design and AI-assisted RSM analysis. Several factors were considered in constructing the prompts, namely a clear language structure, avoidance of biased language, provision of context, and context-based questions (Atlas, 2010). Each prompt was tested three to five times (Supplementary 1). All numerical values produced by the AI models were compared with the RStudio calculations reported by Gonçalves *et al.* (2012), which served as the main reference without modification. Clarification interactions with the AI were standardized by consistently providing information directly related to the dataset structure. During the interactions, the researcher (user) did not provide any information on the RStudio results in order to prevent data leakage into the outputs.

2.4 Comparative Secondary Data Analysis

Statistical parameters were examined using a descriptive comparative approach. The test results and interpretations of each AI model were compared with those of Gonçalves *et al.* (2012), which were based on RStudio. The key parameters in RSM are model significance, goodness of fit, and the coefficient of variation.

3. Results and Discussion

3.1 Building Prompts for AI Chatbots

Good prompts are generally built through three processes, namely prompt initiation, data input, and iteration (refinement); these three processes are the basic principles of prompt engineering (Liu *et al.*, 2023; Park & Choo, 2024). Together, they help establish a good prompt framework (Figure 1). The outputs or answers of the chatbots were assessed by considering whether they were specific and rational. Prompt initiation on both AI models was carried out at the same time for each prompt tested.

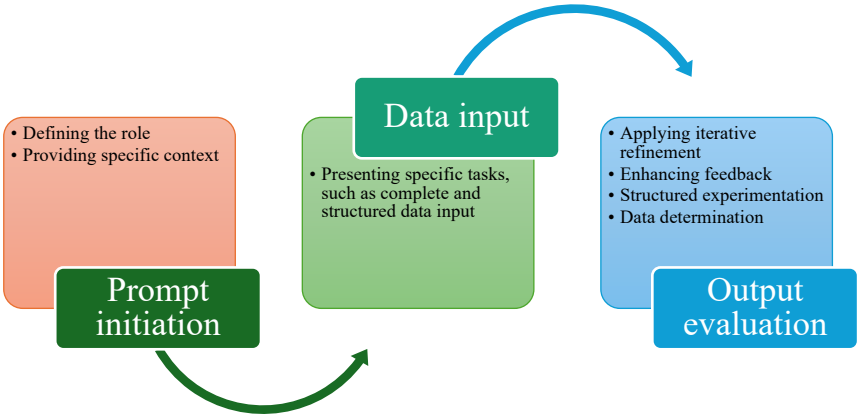

Figure 1. Workflow of prompt construction for AI chatbots

Basically, prompt construction is the most important aspect and requires the intelligence, creativity, and analytical skills of the human user. In this study, the prompts were developed gradually following the flowchart in Figure 1 to obtain instructions capable of producing accurate analytical outputs. Therefore, prompt development was carried out iteratively through repeated trial and error.

Before designing a prompt, it is necessary to understand the forms of prompts. There are two forms of prompts, namely short and long prompts. Short prompts produce less accurate answers because they lack context. In contrast, long and specific prompts contain questions with a broad scope and diverse contexts, so the chatbot answers are more structured, coherent, and complete (Balaji *et al.*, 2024). In this study, short prompts were tested first before long prompts were used (Table 2).

Table 2. Summary of prompts and the outputs generated by AI

Prompt type	AI	Statistical output	ANOVA	Numerical consistency	Indication of hallucination	Notes
Short (general)	ChatGPT	Explanation of the RSM concept	None	Cannot be tested	Not detected	The AI only explained the RSM concept
Medium (data specified)	ChatGPT	Regression model and R^2	Incomplete	Partially consistent	Possibly present	Some values appeared without an ANOVA table
Long (dataset + requested statistical parameters)	ChatGPT	Regression model, R^2, interpretation	Partial	Partially consistent	Indicated	The AI produced statistical values without the full calculation process
Short	Gemini	RSM model equation	None	Cannot be tested	Not detected	The AI focused on the structure of the mathematical model
Short with clarification of response Y	Gemini	Regression model and interpretation	Incomplete	Partially consistent	Possibly present	The AI requested clarification of the response
Revised prompt	Gemini	Model structure and method	None	Cannot be tested	Not detected	The AI explained the computational method

The initial stage used a short prompt, namely "Perform a Response Surface Methodology analysis of the following data" [original: "*Analisis Response Surface Methodology terhadap data berikut*"]. Although the AI systems produced outputs, the analyses were general and the context remained unclear; however, Gemini was able to produce a contour plot (Figure 2b). Next, at the input stage, the prompt was rebuilt in more detail as "Analyze and quantify the RSM data (model significance test (ANOVA), goodness of fit (R square, lack of fit), and coefficient of variation

(CV)) and interpret the overall results" [original: "*Analisis dan kuantifikasi data RSM tersebut (uji signifikansi model (ANOVA), goodness of fit (R square, lack of fit), serta koefisien variasi (CV)) dan interpretasi keseluruhannya*"]. This prompt still produced overfitted analyses, such as R^2 values reaching 80–90% in ChatGPT. The prompt was then further detailed as "Analyze the data quantitatively (the statistical parameters are the estimated model equation (β), factor significance (p value and F value), goodness of fit (R2 and lack of fit), and coefficient of variation (CV)) together with a description (interpretation)" [original: "*Analisis data tersebut secara kuantitatif (parameter statistic adalah persamaan model estimated (β), signifikansi faktor (p value dan F value), goodness of fit (R2 dan Lack of Fit), serta koefisien variasi (CV)) beserta deskripsi (interpretasi)*"], but the answers were still general.

The trial-and-error process continued in two stages, namely initiation and input. At this stage, the prompt was designed as a long prompt with more specific data input: "This dataset is the result of RSM modeling with two factors, namely substrate and time. It is a 5x5 full factorial design, in which substrate concentration 10 was replicated three times, so the total number of runs is 35. There is an estimated product, which is the estimate calculated in R Studio, and an experimental product, which is the laboratory test. The observed response or result is PGL enzyme activity. My question: please calculate the following statistics: - overall RSM model (please find the linear, quadratic, and interaction models) - goodness of fit of the RSM model (R square, lack of fit, and coefficient of variation)" [original: "*Data set ini merupakan hasil dari pemodelan RSM, di mana terdapat dua faktor yaitu substrat dan waktu. ini adalah rancangan 5x5 full factorial, dengan konsentrasi substrat 10 direplikasi sebanyak 3 kali, sehingga total run adalah 35. Terdapat product estimated yaitu estimasi hasil kalkulasi studio R, dan experimental yaitu pengujian di laboratorium. Respon ataupun hasil yang diamati adalah aktivitas enzim PGL. Pertanyaanku, tolong hitung statistik berupa: - over all model RSM (tolong cari Model linear, Kuadratik, Interaksi) - goodness of fit model RSM (R square, lack of fit, dan koevisien variasi)*"]. This prompt produced accurate, specific, and coherent analyses. Therefore, long prompting is a vital point in analyzing RSM with AI.

However, prompting is not the only key point in AI-assisted analysis. At the output evaluation stage, feedback between the user and the chatbot is required. This step is very important and constitutes the main role of humans as users. At this stage, confirmation, questions and answers, and determination of the match between the targeted data and the AI analysis results were carried out (refinement). In one instance in this study, the AI responded to the prompt with a question, so the user had to understand the context of the data provided to the chatbot, as shown in the following conversation:

> ChatGPT: "For this RSM analysis, the response (Y) you want to use is:" [original: "*Untuk analisis RSM ini, respon (Y) yang ingin kamu pakai adalah:*"]
>
> - Production experimental (laboratory results), or [original: "*Production experimental (hasil laboratorium atau*"]
> - Estimated experimental (predicted results of the R Studio model)" [original: "*Estimated experimental (hasil prediksi model R Studio)*"]
>
> User: "Production experimental"
>
> ChatGPT: "All right, this means the RSM model will be built using the experimental production data as the response (Y)" [original: "*Baik, berarti model RSM akan dibangun menggunakan data produksi hasil eksperimen sebagai respon (Y)*"]

In addition to feedback, the user can also refine the output by correcting the prompt so that the AI regenerates its output, as in the following example:

> User: "May I correct the prompt?" [original: "*Boleh ralat prompt?*"]
>
> Gemini: "Of course, go ahead! Which part of the previous question or data would you like to correct or change? Let me know the correction, and I will recalculate the RSM statistics based on the new information or request." [original: "*Tentu, silakan! Bagian mana dari pertanyaan atau data sebelumnya yang ingin Anda koreksi atau ubah? Beri tahu saya*

ralatnya, dan saya akan menghitung ulang statistik RSM berdasarkan informasi atau permintaan yang baru."]

In this study, ChatGPT also asked, "Would you like me to create a contour plot?" [original: "*Apakah mau dibuatkan counter plot?*"]. In response to this feedback, a contour plot was successfully generated, as shown in Figure 2a. Throughout prompt construction, ChatGPT required feedback from the user to validate the output to be generated. In comparison, ChatGPT produced a cleaner visual, whereas Gemini produced a more informative one.

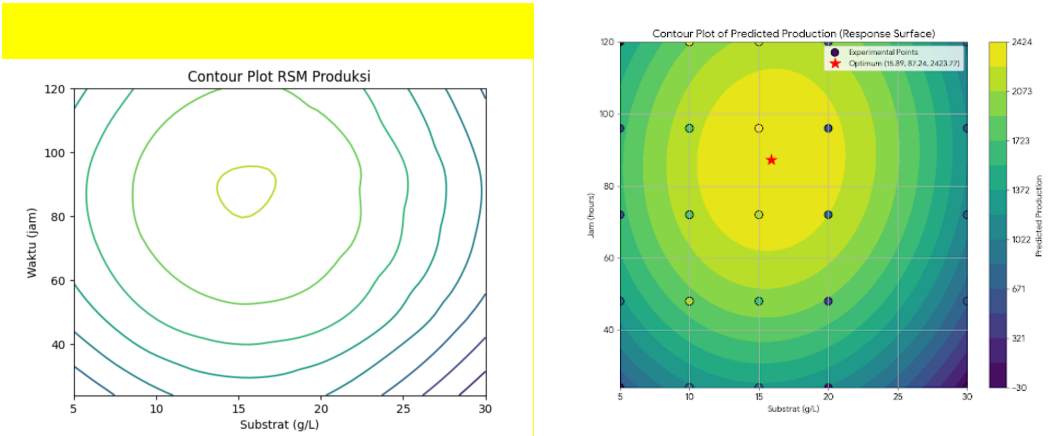

Figure 2. Contour plots generated by (a) ChatGPT and (b) Gemini

Such feedback can help AI improve the accuracy of its analysis. This finding is supported by Retzlaff *et al.* (2024), who reported that human feedback is used in machine agents that learn to make decisions through interaction with their environment (reinforcement learning) to improve models through questions, answers, and confirmation of model outputs. Glickman and Sharot (2025) showed that human–AI interaction influences human judgment; therefore, feedback needs to be controlled so that it remains coherent with the target expected by the user and avoids bias.

3.2 Statistical Analysis and Interpretation of the RSM Model Assisted by AI Chatbots

There are two important parameters for a successful RSM model, namely the regression model and goodness of fit. RStudio was used as the reference for evaluating the AI-assisted statistical analysis.

3.2.1 Regression Model Analysis

The regression models are presented in Table 3. The symbol X denotes the substrate concentration factor, and Y denotes cultivation time. Results were interpreted as significant when the p value was < 0.05.

Table 3. Comparison of the significance tests of regression models obtained from AI and conventional software

Model component	OpenAI ChatGPT	Google Gemini	RStudio (Gonçalves *et al.*, 2012)
Linear model (x + y)	F value 5.57; p value 0.025	F value 5.76; p value 0.0076	p value 0.001
Interpretation	Significant	Significant	Significant
Quadratic model ($x^2 + y^2$)	F value 7.23; p value 0.011	F value 1.30; p value 0.2872	p value 0.001
Interpretation	Significant	Not significant	Significant
Interpretation	Not significant	Significant	Not significant
Overall model	**Significant**	**Significant**	**Significant**

In general, at the overall model level, both AI models showed statistically significant results, with all p values < 0.05. This indicates that the relationship between the independent variables (substrate and time) and the response (pectin lyase activity) can be well explained by the RSM model, regardless of the computational differences between the AI models.

However, there were differences in the analysis of the individual model components. For the linear model (x + y), both AI models produced high F values with $p < 0.05$, and both were interpreted as significant, in agreement with RStudio. Meanwhile, for the quadratic model ($x^2 + y^2$), only Gemini showed a non-significant result ($p = 0.2872$), whereas ChatGPT showed a significant result. For the interaction component ($x \cdot y$), ChatGPT showed a non-significant result, whereas Gemini showed a significant result.

3.2.2 Goodness-of-Fit Analysis

The goodness-of-fit components are presented in Table 4. There are three main components, namely R^2, lack of fit, and the coefficient of variation. The AI models were compared with RStudio as conventional statistical software.

Table 4. Comparison of the goodness of fit obtained from AI and the conventional software RStudio

Goodness-of-fit component	OpenAI ChatGPT	Google Gemini	RStudio (Gonçalves *et al.*, 2012)
R^2	0.4455	0.4357	0.4437
Interpretation	The model explains approximately 44.5% of the variation in the experimental data	43.57% of the response variation is explained by the model	The model explains approximately 44.3% of the variation in the experimental data
Lack of fit	p value 0.0335	p value 0.2289	F value 2.17; p value 0.104
Interpretation	The model does not yet fully describe the actual data pattern	The model adequately describes the experimental data	The model adequately describes the experimental data
Coefficient of variation	38.58%	38.99%	41.14%
Interpretation	Large variation in the experimental data or a relatively high error	High, indicating relatively low experimental precision or large data variability	High, indicating limited precision of the experimental data

The comparison of goodness-of-fit parameters showed that the R^2 values predicted by ChatGPT and Gemini were relatively close to that of RStudio. The lack-of-fit parameter also indicated the adequacy of the RSM model design; however, the interpretations of both AI models indicated a slight mismatch of the RSM model. This interpretation is also in line with the results of the conventional statistical software (RStudio). The calculations of both AI models showed CV values of approximately 38%, which differ only slightly from that of RStudio (differences of 2.56% for ChatGPT and 2.15% for Gemini). This indicates that the RSM model still has relatively high error and data variability.

Compared with the regression model analysis, the same pattern was observed in the goodness-of-fit analysis. The AI models and RStudio provided consistent interpretations, although the numerical values differed. Thus, the numerical differences between the AI systems are presumably due to their inference mechanisms, answer-generation formats, and the probabilistic nature of large language models. The contradictory results between lack of fit and R^2 in the AI models and RStudio reveal weaknesses of AI, including inconsistency in performing computations and reading patterns. Therefore, model building and mathematical calculations should still be validated using conventional statistical programs.

3.3 Model Optimization Assisted by AI Chatbots

In RSM, finding the optimum point is generally the main objective (Montgomery, 2017). Optimization is a process required in every industry, especially for scale-up (Akinyemi *et al.*, 2017). After the regression model and goodness of fit had been obtained, prompting was carried out to examine the potential of AI in predicting the optimum conditions. The prompt used was "Find the optimum combination of X (substrate concentration) and Y (cultivation time) to achieve maximum production" [original: "*Temukan kombinasi X (konsentrasi substrat) dan Y (waktu kultivasi) optimum untuk menghasilkan produksi maksimum*"], which yielded detailed predictions.

The optimum conditions predicted by the two AI chatbots and by RStudio are compared in Table 5.

Table 5. Comparison of the optimum factor combinations obtained from conventional statistical software and two AI chatbots

Factor	RStudio (Gonçalves *et al.*, 2012)	ChatGPT	Google Gemini
Substrate concentration	15.9 g/L	15 g/L	25 g/L
Cultivation time	87 h	96 h	120 h

The output generated by ChatGPT showed a substrate concentration 0.9 g/L lower than that of RStudio and a cultivation time 9 h longer. Meanwhile, Gemini showed differences of 9.1 g/L in substrate concentration and 33 h in cultivation time. However, an interesting finding was observed in the Gemini results. As shown in Table 6, the use of a short prompt in Gemini resulted in differences of only 0.01 for substrate concentration and 0.24 for cultivation time, which are close to the RStudio calculation. However, the output generated by the AI was likely an estimated response based on patterns or an interpretation of the response surface rather than a mathematical calculation.

Table 6. Comparison of Google Gemini calculations using long and short prompts

Factor	RStudio (Gonçalves *et al.*, 2012)	Google Gemini (short prompt)	Google Gemini (long prompt)
Substrate concentration	15.9 g/L	15.89 g/L	25 g/L
Cultivation time	87 h	87.24 h	120 h

3.4 Limitations of AI and AI Hallucination

The comparison of the two AI models (ChatGPT and Gemini) showed their potential for interpreting RSM data, owing to the ability of generative AI to identify general patterns in a given dataset. However, several findings showed numerical values that differed from those of the conventional statistical software RStudio. In general, these differences are not necessarily caused by calculation errors but by the probabilistic way in which AI reads patterns learned during training. Another finding of this study is that the outputs tended to vary depending on the system running at the time of prompting.

Some responses, such as the determination of the optimum point, showed inconsistent values. This phenomenon is assumed to result from AI hallucination, a condition in which the system generates information that appears convincing but is inaccurate and tends to be fabricated. Factors contributing to this phenomenon include limited data during AI training, complex models that are difficult to compute, and the generation process itself (Joshi, 2025). Future studies can minimize AI hallucination by carefully designing the model and applying governance measures such as standardized prompting. In addition, comparisons among AI models and the use of multiple datasets are needed to assess the accuracy of interpretation.

3.5 Practical Implications for Biotechnology

Overall, AI (ChatGPT and Gemini) demonstrated the ability to generate estimates of statistical values close to those of conventional software. However, the results showed differences in calculations between AI and RStudio. This is because AI performs calculations based on patterns learned from the statistical literature during training rather than on mathematical algorithms and numerical computation. Peykani *et al.* (2025) reported that LLM-based AI, such as Gemini, cannot perform specific numerical calculations without adjustment or additional numerical modules.

Nevertheless, AI can provide analysis and interpretation of RSM data. AI is more appropriately positioned as a supporting tool and a decision support system, for example to help interpret the significance results of conventional statistical software. In biotechnology, AI can serve as a "golden tool" for preliminary design, exploration of complex data, simplification of data loads, and as an intellectual "sparring partner" in big data analysis (Gomes *et al.,* 2024). An example of its application in biotechnology is the use of artificial neural network (ANN) algorithms or RSM to optimize fermentation for amylase production (Fernández Núñez *et al.,* 2017). However, AI still has shortcomings in design, such as a tendency toward data bias; therefore, the human role as a user in evaluating chatbot outputs remains important (Gomes *et al.,* 2024).

4. Conclusion

This study was conducted to explore the potential of artificial intelligence (AI) as a supporting tool for the statistical analysis of mathematical models. To date, reports on AI as a supporting tool for interpreting RSM data remain limited. The findings of this study show that prompts play an important role in AI chatbots, but the interaction between the human user and AI is even more important. It can be concluded that prompt construction requires human understanding and critical analysis in interpreting RSM data and outputs. The analyses by ChatGPT and Gemini yielded R^2 values of 43–44%, whereas the conventional analysis yielded 44%, with all overall models being significant. However, the optimization results indicated potential AI hallucination, so AI cannot fully replace conventional statistical software. Therefore, AI serves only as a supporting tool for analysis after mathematical calculations have been performed using conventional statistical software. This study is expected to serve as an initial reference for using AI as a statistical supporting tool, both in designing the biodegumming of natural fibers and in other biotechnology industries.

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6. Declaration of Generative AI

The authors used artificial intelligence (ChatGPT, Claude and Gemini) to assist with the analysis, editing, and language translation of the manuscript.

7. Conflict of Interest Declaration

The authors declare that there are no conflicts of interest regarding the publication of this article. The authors also confirm that this manuscript is original, has not been published previously, is not under consideration for publication elsewhere, and is free from plagiarism.

8. Author Contribution Statement

All authors contributed equally to the conduct research project, data analysis, and writing and preparation of this article.

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